Letters to the Editor

On the Meaning of Fuzzy Approach and Normalisation in Life Cycle Impact Assessment *

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Introduction

Life Cycle Impact Assessment (LCIA) is documented in the form of ISO standards 14040 and 14044 (ISO 2006a, 2006b), giving instructions for LCA practitioners to conduct LCIA applications according to 'good practice'. This framework includes six phases: selection of impact categories, classification, characterisation, normalisation, grouping and weighting. Characterisation according to the ISO standard is considered as the last mandatory step due to its scientific character; in characterisation, different environmental interventions (emissions, resource extractions and land use) should be aggregated to impact category indicator results on the basis of the relevant environmental processes.

The results of LCIA are checked and evaluated in the life cycle interpretation phase in which the aim is to identify significant issues and to evaluate the completeness, sensitivity and consistency of the data from the viewpoint of the scope and goal of a study. The interpretation phase is used to consider if the uncertainty in the assessment is small enough for the results to be reliable.

In general, there are three types of uncertainty that should be considered when estimating the credibility of LCIA results. These are input data, model and trade-off errors. Input data errors are those related to environmental intervention values derived from inventory analysis or other data sources including characterisation factors. Trade-off errors are associated with the determination of weights in weighting. Model errors include choices and assumptions in the model, such as inappropriate selection or aggregation of variables, incorrect characterisation models and boundaries.

Due to the potential errors as outlined above, 'basic' sensitivity analysis is performed in the interpretation phase by varying a single factor (e.g. emissions, characterisation factors, weights) and by observing the effect on the results produced by the model. In the most advanced cases, uncertainty intervals or probability distributions are determined for input variables and the total uncertainty is expressed as a probability distribution by conducting Monte Carlo simulations. However, this approach is time and resource consuming, which is why there is a need to search for alternative approaches, such as the fuzzy theory, to handle uncertainty in LCIA results. Fuzzy logic is an interesting approach for this purpose because it has been successfully applied to different decision situations characterised by uncertainty and imprecision.

In this letter, the results of the fuzzy approach and of the traditional interpretation approach in LCIA are addressed in the context of a case study conducted by Güereca et al. (2007). The differentiation between the results is shown and the reasons for the differences are discussed. The fuzzy approach is also constructed in a way which is consistent with the traditional weighting approach in LCIA. In addition, a further aim of this letter is to illustrate the role of normalisation in LCIA.

1 Materials and Methods

The case study describes five alternatives for biowaste management systems in Barcelona (Güereca et al. 2006b). The options are named as follows 78–22, 67–33, 50–50 , 50–50 du and 100–0. The first number in each option shows the percentage of biowaste collected selectively and the second number shows the percentage of biowaste collected non-selectively. The term 'du' refers to the direct use of wastes (e.g. fish flour) and is used to differentiate the two alternatives 50–50. A starting point for the work by Güereca et al. (2007) is a calculation rule presented by Seppälä and Hämäläinen (2001) used to calculate total impact values based on 'distance to target' valuation, as seen in **Eq. 1**:

$$I(a) = \sum_{i=1}^{n} \frac{N_i}{T_i} \cdot \frac{I_i(a)}{N_i - I_i^{TH}} \qquad (1)$$

where

$I(a)$ = total environmental impact result caused by alternative a

N_i = normalisation reference for impact category i

T_i = target reference of impact category i

$I_i(a)$ = indicator result of impact category i caused by alternative a

I_i^{TH} = threshold reference indicator for impact category i

The normalisation reference (N_i), is the indicator result of impact category i caused by the environmental interventions of a given area. The target reference (T_i) is typically based

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on political issues. The threshold reference indicator describes impact category indicator results above which impacts occur. If threshold reference indicators can be considered zero, Eq. 1 can be written by

$$I(a) = \sum_{i=1}^{n} \frac{N_i}{T_i} \cdot \frac{I_i(a)}{N_i} = \sum_{i=1}^{n} \frac{I_i(a)}{T_i} \tag{2}$$

Eq. 2 corresponds to the equation used in Eco-indicator 99 (Goedkoop 1995). The necessary requirement for both equations is that the target reference values (T_i) within each impact category *i* are considered equal (Seppälä and Hämäläinen 2001). This finding has also been used by Finnveden (1997), Lee (2000) and Finnveden et al. 2002.

Seppälä and Hämäläinen (2001) also showed that both equations can be derived from the following basic aggregation rule in LCIA (**Eq. 3**):

$$I(a) = \sum_{i=1}^{n} cw_i \cdot \frac{I_i(a)}{N_i} \tag{3}$$

where cw_i are impact category weights (i=1,…,n).

To be exact, Eqs. 1–3 can be derived from multi-attribute value theory (MAVT). MAVT is one of the major decision theories for a multi-criteria decision analysis (von Winterfeldt and Edwards 1986), providing a theoretical foundation for calculation rules in LCIA (Seppälä 1999 and 2003).

Normalisation is conducted by dividing impact category indicator results by so-called normalisation factors. Normalisation factors in Eq. 1 are $N_i - T_i^{TH}$, whereas factors in Eqs. 1–2 are N_i. In Eqs. 1–2, impact category weights cw_i can be considered as a ratio between N_i and T_i. According to MAVT weights are typically normalised onto the [0,1] scale so that

$$\sum_i cw_i = 1 \cdot$$

In this letter, impact category indicator results calculated by Güereca et al. (2007) are shown first. The characterisation was conducted by the TRACI model (Bare et al. 2003). In the next step, normalisation is conducted by applying the two normalisation factors described above. The values of normalisation reference and threshold reference indicators were obtained from Güereca et al. (2007). Finally, total impact value scores for each waste management alternative are calculated by Eqs. 1 and 2, in which target reference values presented by Güereca et al. (2007) are used.

The preference orders for the alternatives calculated by Eqs. 1 and 3 were compared with the preference orders obtained by the fuzzy approach presented by Güereca et al. (2007). Instead of using the approach proposed in Eq. 1, they used **Eq. 4**, called partial indicator of impact *i* for alternative *a* [$PIi(a)$]

$$PI_i(a_j) = \frac{N_i}{T_i} \cdot \frac{I_i(a)}{N_i - I_i^{TH}} \tag{4}$$

Next, according to the fuzzy approach, the partial indicator ($PI_i(a)$) within each impact category *i* was normalised onto interval [0,1] by **Eq. 5**:

$$\overline{PI_i(a)} = 1 - \frac{PI_i(a) - PI_i(a)_{\min}}{PI_i(a)_{\max} - PI_i(a)_{\min}} \tag{5}$$

where 0 is the worst and 1 is the best performance.

The fuzzy measurements are defined according to the specific membership functions (shown in **Eqs. 4**, 5 and **6** in the article by Güereca et al. (2007)), where $\overline{PIi(a)}$ is used. Furthermore, in order to measure the fuzzy description of the partial indicators, the membership function for each of the linguistic variables is defined. Considering the linguistic variables e_k (k = 1, …, 11) and the impact categories i (i=1, …, 10), for each alternative a_j (j = 1, …, 5), a matrix $M_{kij} = (e_k(x_{ij}))$ is defined (shown in Eq. 7 of the article by Güereca et al. (2007)). This matrix represents the fuzzy degree of membership of each partial impact to each linguistic variable. The values of x_{ij} are calculated by

$$x_{ij} = \overline{PI_i(a_j)} \tag{6}$$

Finally, in Eq. 6, the decision function $D(a_j)$ permits judgment according to the principle of maximum membership (**Eq. 7**):

$$D(a_j) = \max\left\{\rho^{(k_1)}(a_j), \rho^{(k_2)}(a_j), ..., \rho^{(kn)}(a_j)\right\} \tag{7}$$

$$\rho^{(k)}(a_j) = M_{kij} \cdot W_i \tag{8}$$

where W_i is a vector of impact category weights (w_1 , …,w_{10}) for matrix M_{kij}. In the article, Güereca et al. (2007) did not describe the meaning of this weight vector. They simple omitted the issue assuming that w_i is equal for all the impact categories.

In this letter, the fuzzy approach is constructed in a new way. Instead of using equal weights (w_i) for impact categories in **Eq. 8**, the weights are determined on the basis of transformation used in Eq. 5, in which the information of partial indicators was changed to the [0,1] scale. It is important to notice that partial indicator $PI_i(a)$ for alternative *a* within each impact category *i* in Eqs. 4 and 5 represents an aggregated result in a commensurate unit. The purpose of weights in Eq. 8 is to describe the value differentiations between partial indicators in the commensurate unit. The determination of impact category weights does not require an elicitation process because the transformation in Eq. 5 means, on the basis of MAVT, that the weights can be determined by (see e.g. Salo and Hämäläinen 1997, p. 310)

$$w_i = PI_i(a)_{\max} - PI_i(a)_{\min} \tag{9}$$

Finally, in **Eq. 9**, according to the fuzzy approach, the weights are normalised so that

$$\sum_{i=1}^{10} w_i = 1 \cdot$$

2 Results and Discussion

From the point of view of a decision-maker, the impact category indicator results obtained by characterisation are not sufficient for decision-making in the case study of biowaste management systems in Barcelona (**Fig. 1**). In comparative studies like this it is difficult to conclude whether the alternative 78–22 should be regarded as more harmful than the 100–0 alternative. It can be seen that alternative 78–22 is better than alternative 100–0 in some impact categories, but poorer in others.

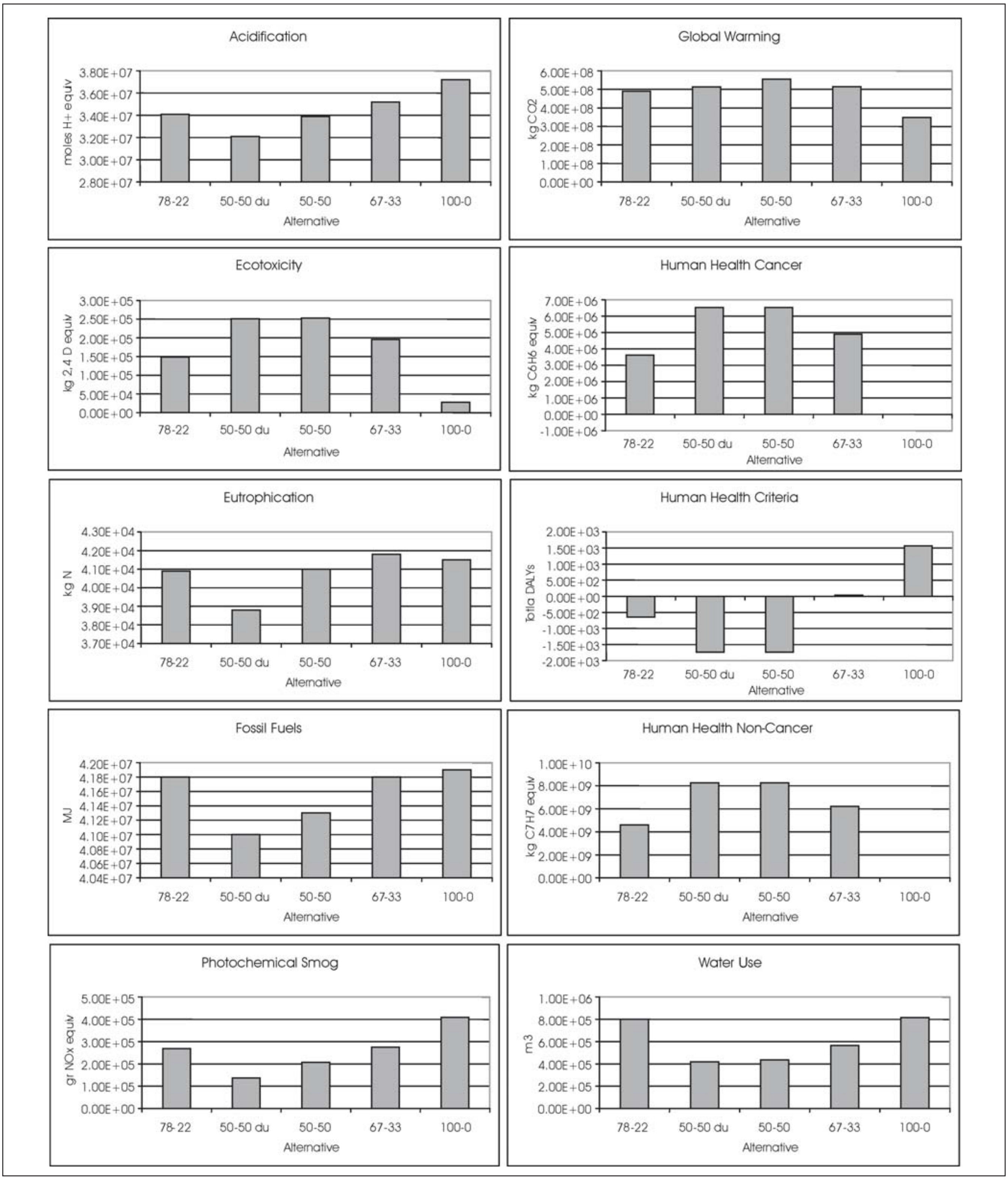

Fig. 1: Impact category indicator results of biowaste management systems in Barcelona (Güereca et al. 2007)

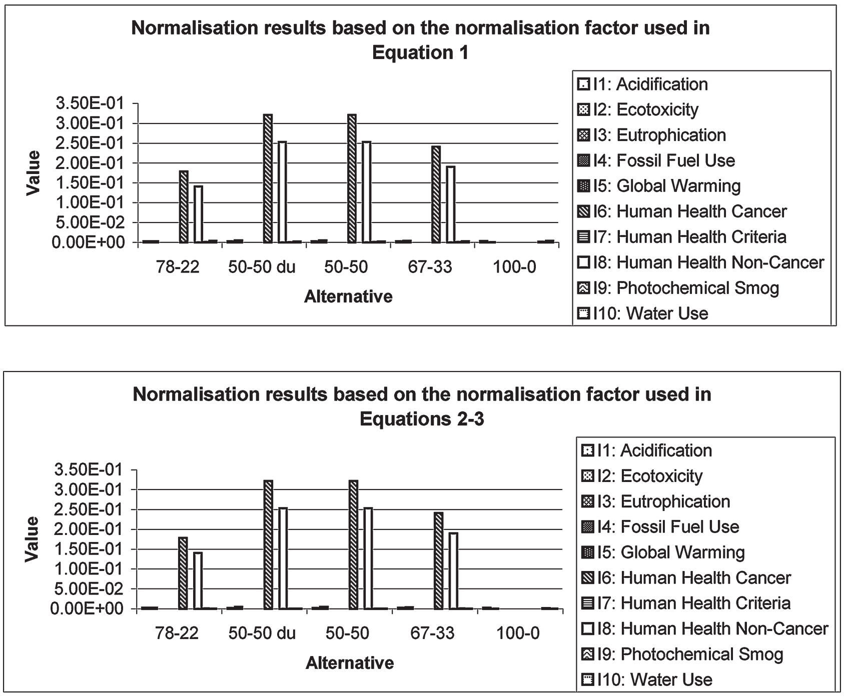

Fig. 2: Normalisation results based on normalisation factors used in Eqs. 1–3

In the case study, the normalisation phase of LCIA can help to interpret the significance of the impact categories in relation to each other. Firstly, the impact category indicator results of the alternative biowaste management systems are divided by the corresponding Catalonian reference values (see Eq. 3). In practice, this so-called traditional normalisation produces the same results as the advanced normalisation rule in Eq. 1 in which impact category indicator results are divided by normalisation references minus threshold reference indicators (**Fig. 2**). The contributions of impact categories 'Human Health Cancer' and 'Non-Cancer' to the normalisation results dominate (see Fig. 2). The alternative 100–0 does not cause the effects of these two impact categories. In practice, the other impact category indicator results do not affect the results.

The normalisation results indicate that the alternative 100–0 is best because normalised values can be interpreted so that the values represent the total impact values calculated by equal impact category weights for all impact categories (Seppälä and Hämäläinen 2001). It is also important to understand that a decision-maker should determine impact category weights on the basis of a rule in which impact category effects caused by normalisation factors are weighted against each other (Seppälä and Hämäläinen 2001). By varying inventory data and impact category weights, it can be seen that the preference order of the alternative 100–0 does not change easily; even with large uncertainty intervals in inventory data, characterisation factors and weights, the alternative 100–0 has the lowest impact value, i.e. it is a best alternative (the higher the value, the more harmful the effect on the environment). The low total impact value of alternative 100–0 can also be easily shown by calculating total impact values according to Eq. 1 (**Fig. 3**). In practice, Eq. 2 produces the same total impact values as Eq. 1. Even by using equal weights and the traditional normalisation in the aggregation rule (Eq. 3) the total impact value scores of the alternatives do not change significantly (see Fig. 3). The preference order is 100–0 > 78–22 > 67–33 > 50–50d=50–50. However, the order is completely different when compared with the results calculated by the fuzzy approach of Güereca et al. (2007), in which impact category weights in Eq. 8 were considered as equal. They received the preference order 50–50 du > 78–22 > 67–33 > 50–50 > 100–0.

The fuzzy approach produces exactly the same preference order as the traditional weighting in LCA (Eqs. 1–3) when non-equal impact category weights calculated on the basis of Eq. 9 are used in the fuzzy approach (**Table 1**).

The reason for the difference in the results of the two fuzzy approaches is clear. Equal impact category weights, in Eq. 8, cause the wrong priorities for the alternatives.

It is important to note that, although the new fuzzy approach and the traditional aggregation rule in LCIA lead to the same preference order, the results can change due to the uncertainty of input data used in Eq. 1, especially concerning the alternatives other than 100–0. However, this discussion is not considered in this paper.

3 Conclusions and Questions

The case study of biowaste management systems in Barcelona shows, in practice, that characterisation results are impossible to interpret due to the proxy units of impact category indicator results. The normalisation phase can clarify the significance of impact category indicator results as can be seen in this case study. Furthermore, after normalisation, it

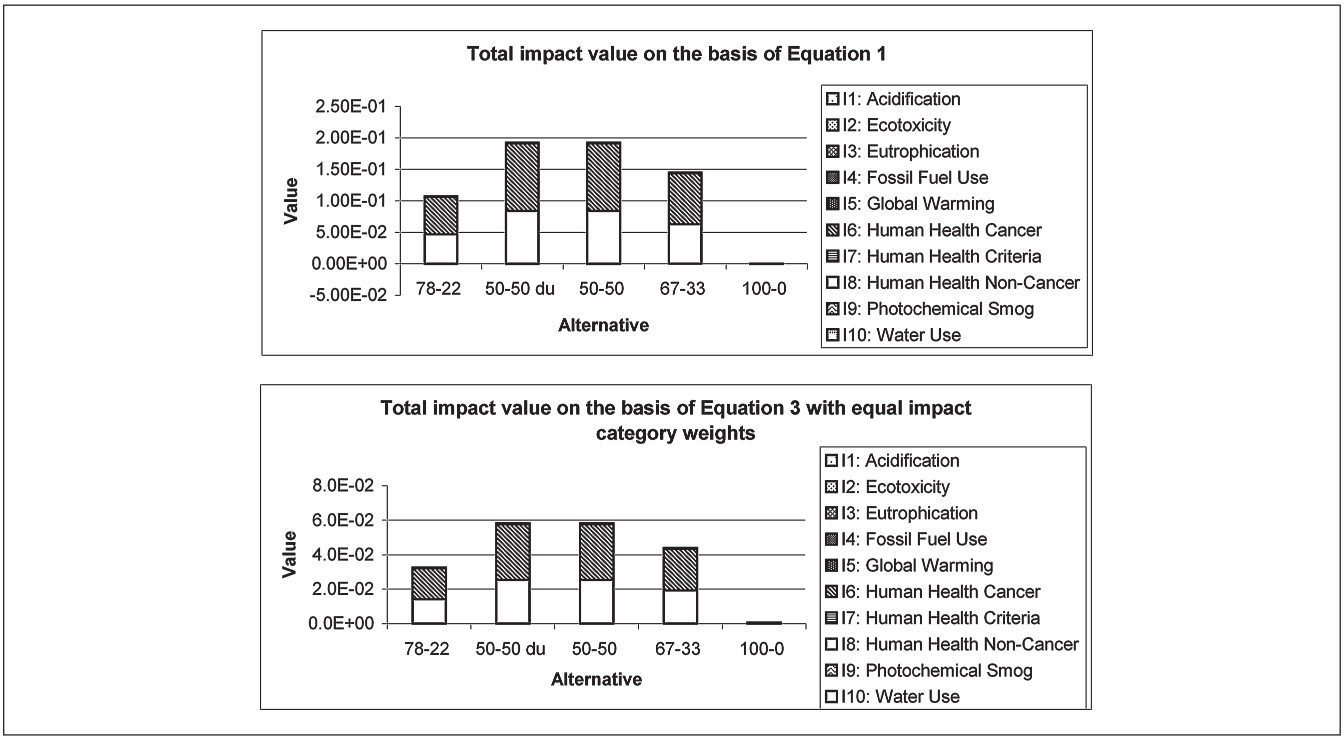

Fig. 3: Total impact values for biowaste management systems calculated by Eqs. 1 and 3. In the context of Eq. 3 equal impact category weights were used

Table 1: Values of the decision function. The highlighted boxes show the maximum membership

Scenarios / Semantic term	78–22	50–50 du	50–50	67–33	100–0
Terrible	0.000	0.999	1.000	0.000	0.000
Very, very bad	0.000	0.001	0.000	0.000	0.000
Very bad	0.000	0.000	0.000	0.502	0.000
Bad	0.000	0.000	0.000	0.498	0.000
Quite bad	0.552	0.000	0.000	0.000	0.000
Not so good	0.448	0.000	0.000	0.000	0.000
Quite good	0.000	0.000	0.000	0.000	0.000
Good	0.000	0.000	0.000	0.000	0.000
Very good	0.000	0.000	0.000	0.000	0.000
Very, very good	0.000	0.000	0.000	0.000	0.000
Excellent	0.000	0.000	0.000	0.000	0.000
Very, very, very good	0.000	0.000	0.000	0.000	1.000

is possible to calculate total impact value scores by multiplying normalised results by impact category weights. According to multi-attribute value theory (MAVT) reference values used in normalisation offer a clear basis for the valuation of impact category weights. In addition, it is important to note that normalised values describe exactly the same differences between alternatives within each impact categories as impact category indicator results do.

How can a decision-maker directly weight impact category indicator results? According to MAVT, this means that a decision-maker is capable of weighting the units of impact category indicators against each other. However, this is a very difficult task. It is much easier to weight the effects of impact categories caused by Europe (or Catalonia) against each other. Furthermore, it is quite easy to assume that decision-makers or even LCA practitioners try to apply equal weights for the interpretation of characterisation results. This can lead much easier to the wrong interpretation compared with the approach using equal weights for normalised values. The question arises: why does normalisation not belong to the mandatory phase in ISO standards?

The key issue in the fuzzy approach is how to determine impact category weights for the final preference order calculations. It is important to understand that impact category weights in the context of the fuzzy approach have a different meaning compared with the meaning of impact category

weights in a typical aggregation rule used in LCIA. In addition, it is somewhat unclear what the additional value of the fuzzy approach in the interpretation of LCIA results is, when compared with the traditional approach in which input values and model structures are varied according to their uncertainty aspects. Is it a good practice to replace the uncertainty information of inventory data and characterisation factors by fuzzy information? Maybe the fuzzy approach can be used as an additional interpretation tool for LCIA, but it can not replace the attempts to understand which parts of the LCIA include the most uncertainty.

This letter has shown that MAVT can assist in an understanding of which are 'good' approaches to LCIA and in the interpretation of LCIA results. However, the LCA community is not familiar with MAVT and its possibilities in the development of LCIA on the basis of its axiomatic foundation. Of course, there are many other attractive decision analysis methods and theories which can also be helpful for the development and interpretation of LCIA.

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Fuzzy Approach to Life Cycle Impact Assessment

An Application for Biowaste Management Systems

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Abstract

Background, Aims and Scope. In LCA the valuation step is very controversial since it involves value judgments. In order to strengthen the valuation step, this work establishes a new method, which includes normalization and weighting. Inspired by the proposal of Seppälä and Hämäläinen (2001), and based on the fuzzy sets theory (Zadeh 1965), this methodology permits information to be processed under uncertainty and subjectivity. The method proposed is applied to valuate five biowaste management system scenarios in the Metropolitan Area of Barcelona.

Methods. The valuation methodology proposed consists of the acquisition of partial environmental impact indicators, calculated on the basis of a characterized impact indicator (results from an LCA), an emissions inventory of the studied region, as well as the political targets and sustainability thresholds for a given area. Next, the partial indicator obtained is transformed to obtain a fuzzy linguistic descriptor, which permits the construction of a preference order amongst a series of alternatives.

Results. The proposed methodology permits the LCA normalization and weighting to be considered using a mathematically strengthened approach. It considers a semantic scale with eleven terms, which permits the gradual definition of the performance of alternatives according to their level of membership.

Discussion. This consideration deals with the uncertainty and subjectivity inherent in the data used. The results reveal that the worst biowaste management option is the scenario where all biowaste is collected selectively and treated only with biological processes. The preferred biowaste management scenario is the one in which direct uses of biowaste are considered.

Conclusions. The fuzzy approach considered improves the theoretical strength of the value obtained by the Distance to Target (DtT) method and its modification in accordance with Multi-Attribute Value Theories (MAVT). This permits the evaluation of complex systems, which are frequently placed in the field of subjectivity and uncertainty. This is therefore a good method of supporting the decision-making process, based on life cycle impact assessment results. In addition, the order of preferences obtained is consistent with the characteristics of each of the scenarios analyzed.

Recommendations and Perspectives. As future work, it is recommended that this methodology be applied to other situations, both in order to analyze its functionality and to compare the process defined with other fuzzy approaches, which may be appropriate for the valuation step in LCA.

Keywords: Biowaste management; decision-making; fuzzy sets theory; LCIA; multi-attribute value theory; valuation; weighting